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Geographically weighted regression modeling of spatial and temporal evolution characteristics of urban-rural landscapes

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Abstract Ecological land use is crucial to the sustainable development of urban areas. This study takes the ecological land in three counties and cities of Baiyangdian in North China as the object, and adopts the methods of land-use dynamic attitude, remote sensing image interpretation, land-use transfer matrix, Moran's index and geographically weighted regression model to statistically analyze the spatial and temporal evolutions and spatial differentiation laws of each ecological land, and to quantitatively describe and detect the changes of landscape structural characteristics in different time periods. The results show that: from 2014 to 2019, the total area of cultivated land decreased slightly, the area of forest and grassland increased gradually, and the area of construction land increased substantially. In terms of the overall landscape type structural transformation, it mainly occurs between cropland, forest and grassland, and construction land.The difference in the area of forest land increases in 2014-2024, and the diversity and complexity of ecosystems increase.

Index Terms land use dynamics, Moran index, geographically weighted regression model, spatial and temporal evolution

I. Introduction

With the policy guidance of urbanization and rural development and other aspects, the study of urban and rural landscape has significant theoretical and practical significance [1]. At present, with the rapid development of urbanization, rural construction has been carried out one after another, which has brought about blind expansion of construction land and disorderly use of land while promoting rural economic development and rural transformation, thus causing a series of problems such as difficulty in securing basic arable land, environmental deterioration and ecological crisis, imbalance of landscape pattern, and loss of landscape characteristics [2]-[5]. On the contrary, irrational land use in the process of rural development directly affects the spatial pattern of rural landscape, resulting in the inability of the rural natural system to circulate normally and the damage of the ecological balance system, which in turn seriously affects the sustainable development of the countryside.

Under the background of rapid urbanization, with the rapid expansion of urban economy and population scale, urban land is gradually expanding to the periphery in different forms, and the central city is gradually radiating to the periphery, driving the development of the surrounding area, forming a large urbanized area, and at the same time, forming a large urban-rural intertwined area at the edge of the city [6], [7]. In this context, the sustainable ecological development of the city is hindered, and the cultural landscape heritage suffers damage, the number of intact landscapes declines rapidly, the problem of semi-urbanized landscape zones is highlighted, its economic value is reduced, as well as the influence of urban transportation and political status, etc., and the landscape pattern of the city undergoes rapid changes [8]-[11]. The speed of urban land use conversion is fast, while its conversion trend has a more obvious unidirectional character, and there is a phenomenon that other land use types are rapidly converted to urban construction land [12]. Therefore, the qualitative, quantitative, temporal and spatial analysis of this typical space of urban rural landscape has important theoretical and practical significance for the study of the landscape pattern of the relevant typical areas.

The geographic regression weighting model combines the weight of each sample point with its geospatial correlation by using a geographic weighting matrix. The geographic regression weighting model can be used to solve the problems that cannot be solved by the traditional regression model, including the existence of spatial non-independence and spatial heterogeneity among the sample points, and it has been widely applied in the fields of traffic flow analysis, urban planning, environmental assessment, and land use, etc [13]-[16].

In this paper, the use of land use transfer matrix and the attitude of land use dynamics in the two different periods, the same spatial location, different land types of the conversion of the transfer of the direction and transfer of the nature of the description of the situation, reflecting the land use types of area changes. Through the geographically weighted regression model and Moran index analysis, the sample point location information was added to the regression parameters to explore the relationship and correlation between variables that varied with spatial location. Under the ArcGIS 10.7 system software, the landscape pattern index was utilized to quantitatively describe and detect changes in landscape structural characteristics in different time periods. In this study, the ecological land in three counties and cities of Baiyangdian in North China is taken as a research sample, and by using the above research methods, thus exploring the spatial and temporal evolution characteristics of the landscape of Baiyangdian.

II. Data processing and research methodology

Rural landscape refers to the products of human-land interaction with specific landscape behaviors, forms and connotations within the rural area, and is the spatial representation of the composite ecosystem composed of humanistic, economic and natural environments of the rural society, with the composite characteristics of humanity and nature. Under the wave of globalization, industrialization and modernization after World War II, the population, industry, social structure and ecological pattern of rural areas have been profoundly reshaped. Under the implementation of the European Common Agricultural Policy, the western rural areas have generally experienced the development process from agricultural intensification, agricultural scale expansion to the abandonment of marginal agriculture, and the rural landscapes have realized the transformation from “productivism to post-productivism, from production space to consumption space, and from idyllic landscape to post-instructional landscape”. The evolution of rural landscapes, which integrates the multidisciplinary scope of multifunctionalism and the concept of sustainable development, is characterized by regionalization and diversification, and the transformation of rural land functions drives the evolution of rural landscape structures, types and functions. Under the dominance of multiple values, agricultural functions are no longer the main form of the economic foundation of the countryside, and the evolutionary trajectory of multifunctional transformation of rural landscapes is full of dynamism, complexity and heterogeneity, with a focus on the rural community and social equity, as well as taking into account the comprehensive values of rural social-ecological system service functions and spiritual and cultural values, and promoting the exploration of sustainable rural development with humanism at its core.

II. A. Data sources and processing

The land use remote sensing data were obtained from the Chinese multi-period land use remote sensing monitoring dataset of the Center for Resource and Environmental Science and Data of the Chinese Academy of Sciences (https://www.resdc.cn/DOI/), and the data for each period were mainly used Landsat8 OLI remote sensing imagery data, with a spatial resolution of 30 m. In order to ensure the reliability of the results of the study, it is necessary to perform Pre-processing, geometric correction, atmospheric correction, and image mosaicing were performed by remote sensing image processing platform ENVI5.1. The supervised classification method of maximum likelihood method is used to supervise the classification of remote sensing image data to generate the landscape land use distribution map. Finally, the accuracy of the classification results was verified, and the overall classification accuracy was above 90%, and the Kappa coefficient was above 0.8, which meets the accuracy requirements for classification data in this study. According to the field research and land utilization, the landscape types are divided into five types: arable land (dry land, paddy field, etc.), forest land, construction land (town land, township settlement, etc.), grassland and water, and then the area proportion of different land use landscape types is partitioned and counted. Using ArcGIS10.7 software to transform the three-phase vector map of land use types into raster map, respectively, intersection analysis can be obtained in each period of time landscape type transfer matrix, and once again raster map imported into Fragstats4.2 software to calculate the landscape pattern index.

II. B. Research methodology

II. B. 1) Landscape pattern index

Landscape pattern index is used to quantitatively describe and detect changes in landscape structural features in different time periods. With the support of ArcGIS 10.7 system software, the landscape pattern indices were analyzed using the landscape pattern analysis software Fragstats to derive results about landscape pattern indices. In this study, a total of 12 landscape pattern indices were selected based on the overview of the study area and the ecological significance of each landscape pattern index. Among them, six indices were selected from the type level, which were patch type area (CA), patch type percentage (PLAND), number of patches (NP), patch density (PD), maximum patch index (LPI) and landscape aggregation index (AI). Six indices were selected from the landscape level, namely, number of patches (NP), Shannon diversity index (SHDI), Shannon evenness index (SHEI), spread index (CONTAG), landscape aggregation index (AI), and scatter and juxtaposition index (IJI) [17].

II. B. 2) Land-use dynamics

The attitude of single land-use dynamics (LK) can reflect the change in the area of each land-use type during the study period, indicating the annual rate of change of a certain land-use type. Comprehensive land use dynamics (LC) can reflect the overall rate of change of all land types in the study area during a certain study period, indicating the annual rate of change of comprehensive land use change in the study area [18]. The calculation formula is as follows:

$$LK = \frac{U_b - U_a}{U_a} \times \frac{1}{T} \times 100\% \tag{1}$$

$$LC = \left(\frac{\sum_{a=1}^{n} \Delta LU_{a-b}}{2\sum_{a=1}^{n} LU_a} \right) \times \frac{1}{T} \times 100\% \tag{2}$$

where: U_a and U_b are the area of the land type at the beginning and the end of the study area $\left(km^2\right)$, and T is the length of the study period. LK is the single-motion attitude of a land use type during the study period. LU_a is the area $\left(km^2\right)$ of the a th land use type at the beginning of the study period. ΔLU_{a-b} is the absolute value of the sum of the area of the a th land use type transformed to other land use types at the beginning of the study. n is the total number of land use types in the study area.

II. B. 3) Land-use transfer matrix

The land use transfer matrix is a commonly used method to measure regional land use changes, which visualizes the trend of each land use type and the area of different land use transfer directions in the study area [19]. This study used the raster calculator tool in ArcGIS10.7 to overlay land use raster data processing to get the conversion between different land types, and used Excel to summarize to get the land use transfer matrix model as follows:

$$S_{pq} = \begin{bmatrix} S_{11} & \cdots & S_{1m} \\ \vdots & & \vdots \\ S_{m1} & \cdots & S_{mm} \end{bmatrix} \tag{3}$$

where: p and q are the land use types at the beginning and end of the study, respectively. m is the total number of land use types. S_{pq} is the total area converted from type p to type q during the study period.

II. B. 4) Spillover analysis based on the Moran index

The Moran index was introduced to analyze the correlation between construction land and cropland in the study area, in which the global Moran index can analyze the overall spatial correlation between construction land and cropland, and the local Moran index can effectively analyze the spatial correlation between construction land and cropland in a small-scale range [20]. The calculation of global and local Moran's index is shown in equations (4) and (5), respectively:

$$I = \frac{n}{S_0} \frac{\sum_i \sum_j w_{ij} Z_i Z_j}{\sum_i Z_i^2} \tag{4}$$

$$I_i = \frac{Z_i}{S^2} \sum_{j \neq i}^{n} w_{ij} Z_j \tag{5}$$

$$Z_i = y_i - \overline{y}, Z_j = y_j - \overline{y},$$
$$S^2 = \frac{1}{n}\sum(y_j - \overline{y})^2, S_0 = \sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij} \tag{6}$$

In the formula, n denotes the number of expropriated land type patches, y_i and y_j denote the land type of the i th and j th patch, respectively, and w_{ij} is the weight. When the Moran index I is positive, it indicates a positive correlation, and a negative value indicates a negative correlation. Absolute values are taken for I, the larger the value the stronger the correlation. When I_i is positive, it indicates that the i th patch and its neighboring attribute values are all high (high - high) or attribute values are all low (low - low). If I_i is negative, it indicates that the i th patch and its neighboring attribute values are both high (high - low) or low (low - high).

II. B. 5) Geographically weighted regression models

MGWR (multi-scale geographically weighted regression) is an extended application of the GWR (geographically weighted regression) model so that the respective variables use their optimal bandwidths, which can have estimation of data with spatial autocorrelation and can reflect the spatial heterogeneity of the parameters in each research unit. Therefore, the study used the MGWR model to quantitatively identify the mechanism of different drivers on the green transformation indicators of cultivated land in Shandong Province, and the regression coefficients of the drivers reflect the spatial response relationship of the green transformation indicators of cultivated land to them [21].

The calculation formula is as follows:

$$y_i = \sum_{j=1}^{n} a_j x_{ij} + \sum_{j=n+1}^{m} \beta_j(u_i, \gamma_i) x_{ij} + \varepsilon_i \tag{7}$$

In Equation (7): y_i denotes the dependent variable of the i th grid, a_j is the regression coefficient of the global variable, and n is the number of grids. (u_i, γ_i) is the coordinates of the center point i of the grid, m is the number of independent variables, β_j denotes the regression coefficient of the local variable, and x_{ij}, and ε_i are the observed value of the j th independent variable at location i and the random error term, respectively.

III. Results and analysis

III. A. Overview of the study area

Baiyangdian is the largest freshwater lake in North China. Baiyangdian area involves five counties and cities in Baoding City and Cangzhou City, including Anxin County, Rongcheng County, Xiong County, Gaoyang County and Renqiu City, with a total area of about 3,089 km², which is located in the middle of the plains of Hebei Province, at the eastern foot of the Taihang Mountains, and belongs to the southeastern part of Baoding City and the northwestern part of Cangzhou City, connecting with Baoding City to the west and adjoining with Bazhou City of Langfang and Wen'an County to the east. Baiyangdian is rich in freshwater and land resources, dominated by flat wetlands, lakes and farmland, with abundant and crisscrossing water systems.

III. B. Changes in landscape scale and structure

III. B. 1) Landscape scale changes

In terms of the scale of rural natural landscape as shown in Table 1, the landscape type of Baiyangdian area has changed significantly. Specifically, from 2014-2019, the change of arable land is small, and the total area is slightly reduced.From 2019-2024, the change of arable land is large, and the total area of arable land in this period is reduced by 720.59km², with a rate of change of 33.53%.From 2014-2024, the arable land area ratio of all types decreased from 2148.95 to 1224.63. 2014-2019, the area of forest and grassland increased gradually. 2019-2024, the growth of forest and grassland area climbed, during which the area of forest and grassland area increased by a total of 648.28km², with a rate of change in area of 83.29%. The ratio of forest and grassland to all types of area grows from 130.08 to 778.36 in 2014-2024, and the reduction of arable land is mainly transformed into forest and grassland and construction land.The area of construction land grows considerably in 2014-2024, and the ratio of construction land to the total type of area grows from 512.63 in 2014 to 722.54 in 2024.Especially in 2019-2024, the construction land area in Anxin County, Rongcheng County and Xiong County area expands rapidly, growing by a total of 209.91km². The main landscape types of Baiyangdian wetland are aquatic vegetation and open water body.From 2014 to 2024, the area of aquatic vegetation increases gradually, with an area growth rate of 34.73%, especially in 2014-2019, with an increase of 63.79km². The area of open water body shows a trend of decreasing and then increasing, compared with 2014, the area of open water body in 2024 increased by 23.82km².From 2014 to 2024, the area of bare land in Baiyangdian area gradually decreases, and the ratio of bare land to the area of all types decreases from 60.45 to 27.45.

Table 1: Rural natural landscape type area changes

Project	Year	Ploughing	Grass land	Construction land	Aquatic vegetation	Open water	Bare land
Area/km²	2014	2148.95	130.08	512.63	148.46	104.25	60.45
	2019	1945.22	243.89	592.06	212.25	82.96	32.09
	2024	1224.63	778.36	722.54	227.48	128.07	27.45
Area change/km²	2014-2019	-203.73	113.81	79.43	63.79	-21.29	-28.36
	2019-2024	-720.59	534.47	130.48	15.23	45.11	-4.64
	2014-2024	-924.32	648.28	209.91	79.02	23.82	-33
Annual rate of change/rate	2014-2019	-9.48	14.62	11.00	28.04	-16.62	-46.91
	2019-2024	-33.53	68.67	18.06	6.70	35.22	-7.68
	2014-2024	-43.01	83.29	29.05	34.73	18.60	-54.60

III. B. 2) Transformation of landscape structure

During the study period, the most obvious change in landscape type is from 2019 to 2024, which is concentrated in the change of cultivated land, forest and grassland, and construction land, which is mainly due to the development concept of “planting greenery first, then building a city” in Xiongan New Area. In order to clarify the landscape structure changes caused by the transformation relationship of each landscape type in the Baiyangdian area, the structural transformation characteristics of various landscape types in the Baiyangdian area were analyzed according to the three time phases of 2014-2019, 2019-2024, and 2014-2024, as shown in Table 2. Shown.

Table 2: Rural natural landscape type transfer matrix

Year	Natural landscape type	Ploughing	Grass land	Construction land	Aquatic vegetation	Open water	Bare land
2014-2019	Ploughing	178432	73.56	23.36	22.96	6.29	24.08
	Grass land	185.62	32.58	9.25	7.05	6.39	5.49
	Construction land	9245	13.12	470.85	3.89	2.15	11.07
	Aquatic vegetation	62.78	9.28	5.36	104.85	25.48	5.19
	Open water	3.46	1.58	5.38	10.63	62.98	2.08
	Bare land	15.48	1.57	1.82	0.39	0.28	12.98
2019-2024	Ploughing	1078.56	96.58	27.78	20.14	0.99	9.67
	Grass land	582.62	96.54	26.78	19.24	0.99	9.78
	Construction land	192.08	100.85	63.89	19.48	1.64	10.48
	Aquatic vegetation	62.22	26.78	492.51	4.48	2.78	8.94
	Open water	15.08	11.48	10.56	132.89	9.85	1.84
	Bare land	20.98	7.04	2.04	35.84	68.62	082
2014-2024	Ploughing	1130.05	38.62	16.58	17.58	3.48	17.05
	Grass land	648.45	57.52	45.53	7.12	3.32	15.89
	Construction land	242.22	20.45	441.98	3.94	2.94	18.32
	Aquatic vegetation	85.36	9.92	9.94	98.54	16.48	5.62
	Open water	20.53	3.89	3.45	20.01	77.32	3.71
	Bare land	22.94	0.94	1.54	0.56	0.04	0.52

From the perspective of overall landscape type structural transformation, the landscape type of the study area mainly occurs in the transformation between cropland, forest grassland, and construction land. The new growth of forest and grassland is mainly converted from cropland and construction land, of which cropland contributes the most, and it is also the impact of the “Millennium Show Forest” project in Xiongan New Area that makes a large amount of cropland to be converted. 2014-2019, the reduction of cropland area is shifted to forest and grassland, construction land and aquatic vegetation, while the growth of aquatic vegetation is increased by 1.2%. The increase in aquatic vegetation is mainly due to the conversion of open water bodies and cultivated land, indicating that the wetland ecological situation in Baiyangdian has improved significantly in this period, with active protection of forest grasslands and waters.

III. C. Characteristics of spatial and temporal evolution of landscape pattern indices

The different landscape type areas in Baiyangdian District are shown in Table 3, and the woodland landscape is always dominant from 2014 to 2024, with a woodland area of 9,753.89hm² in 2024, maintaining a high coverage rate. Residential land is dominated by village settlements, and the area of villages increases to 293.68hm² after urbanization. The area of dry land decreases from 1945.98hm² to 1530.28hm². The area of paddy fields, as the core landscape, shrunk from 4804.362hm² to 3752.14hm², and the overall trend of paddy fields and drylands is decreasing. The water body shifted from point distribution to line distribution in the north, east and west, with the area increasing from 10.84hm² to 70.94hm². With the continuous development of mass tourism, the demand for water resources expands due to the increase in agriculture, local operators and foreign operators, so the flow distribution of water resources becomes wider. Grassland area shrinks from 736.35hm² to 302.98hm², which is gradually replaced by garden land, dry land and forest land. In summary, the land use type is increasing from 2014 to 2024, and the forest and village landscapes are stabilized in the tetrapod isomorphism. The water system becomes more widely distributed because of the expansion of the use demand.

Table 3: Different landscape type area

Landscape type	2014	2024
Woodland	8512.74	9753.89
Water field	4804.36	3752.14
Arid land	1945.98	1530.28
Grass	736.35	302.98
Garden land	425.97	664.78
Residential land	278.68	293.68
Water	10.84	70.94
Industrial and mineral storage	9.56	7.38
Other land	14.46	15.28
Transport land	0	23.56
Public management services	0	27.29
Commercial services facilities	0	184.47
Special land	0	2.59

The dynamics of landscape pattern indices in Baiyangdian district in terms of discrete, heterogeneity and complexity are shown in Table 4. Woodland is the dominant matrix of the terraced landscape, and its AREA_CV value increased significantly in 2024, reflecting the increase in area differences and the enhancement of ecosystem diversity and complexity. Meanwhile, the ENN_AM value of woodland decreased and SPLIT value decreased, indicating increased connectivity and lower separation. The ENN_AM values of paddy fields, drylands, grasslands, residential lands, and garden lands were decreasing compared to 2014, and the distribution of patches became dense with stable changes in connectivity, indicating that the ecological connectivity of landscape patches in these categories was increasing. Water flow channels play the role of connecting patches to help species migration, and ecological flow can be considered as a kind of corridor, with the increase of water area, SPLIT value is decreasing, reflecting the degree of separation is decreasing. The landscape matrix has a positive influence on the distribution and function of patches and corridors with increasing values of the patch index. However, in 2024, patch shape complexity and self-similarity decreased, and SPLIT values for major landscapes, such as paddy fields, increased, indicating an increase in the degree of separation of patches.From 2014 to 2024, SHDI values decreased slightly, and the overall change was small, indicating a small change in the degree of fragmentation. The woodland ecosystems in the landscape matrix provide a stable water-holding function for the entire rice farming system, while supporting water channels to connect the ecological patches and maintain the continuity of biological flows and ecological processes. The landscape pattern before and after the Baiyangdian area is generally dynamic and stable, but with the influence of human activities, the complexity of various landscape patches has significantly decreased and the separation of major landscape patches has increased compared with the pre-heritage period. Increased fragmentation of the terraces will lead to loss of habitat, decreased biodiversity, disturbed water cycle management, weakened landscape connectivity, and damage to the ecosystem.

Table 4: The landscape pattern index in the district of the year

Year	Type	AREA_CV	FRAC_MN	ENN_AM	SPLIT	SHDI	NP
2014	Woodland	1420.984	1.0287	62.198	9.612	12669	1650
2014	Water field	922.9582	1.0664	64.002	37.162		
2014	Grass	394.784	1.0919	314.879	3630.811		
2014	Arid land	322.306	1.0978	88.516	211410.736		
2014	Residential land	132.814	1.0217	289.563	20365.869		
2014	Garden land	174.528	1.0860	200.154	14869810.23		
2014	Industrial and mineral Storage	106.837	1.0381	622.115	20297236.83		
2014	Water	130.622	1.0492	378.822	7528894.096		
2014	Other land	116.958	1.0380	920.689	3384.6		
2024	Woodland	2561.635	1.0362	60.407	112.905		
2024	Water field	867.201	1.0954	62.987	25210.872		
2024	Grass	417.526	1.1097	117.502	5032.674		
2024	Arid land	433.839	1.0379	84.798	254089.0891		
2024	Residential land	178.615	1.1058	126.487	3496.300		
2024	Garden land	417.189	1.0581	80.689	40422153.35		
2024	Industrial and mineral storage	112.2009	1.0806	1145.162	40426178.36		
2024	Water	204.468	1.0587	162.847	4783728.069		
2024	Other land	169.326	1.0963	433.251	17622942.78		
2024	Transport land	84.869	1.0221	99.332	7028840.964	12428	4645
2024	Public management services	178.924	1.0668	232.612	9846134.022		
2024	Commercial services facilities	142.945	1.0632	181.247	8045822.847		
2024	Special land	47.265	1.0304	1074.485	578784032.3		

IV. Conclusion

In this paper, we used land use dynamics, remote sensing image interpretation, land use transfer matrix, Moran index and geographically weighted regression model to analyze the evolution patterns and dominant influencing factors of ecological land use in three counties and cities of Baiyangdian in North China from 2014 to 2024, with a view to protect the ecological land use and enhance the value of ecological services in the study area. The results show that: the landscape type of Baiyangdian area has changed considerably. Specifically, from 2014 to 2019, the change of cultivated land was small, and the area of forest and grassland as well as the area of construction land kept growing. The conversion of type structure mainly occurred between cultivated land, forest grassland, and construction land. The AREA_CV value of forest land in Baiyangdian area increased significantly during 2014-2024, meanwhile, the ENN_AM value of forest land SPLIT value and decreased. Patch shape complexity and self-similarity decline in 2024.

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